



# **Where the dust settles: a spatial investigation of respiratory disease and particulate air pollution in the Tamar Valley (1992-2006)**

by

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A thesis submitted in partial fulfilment of the requirements for a Graduate Diploma in Spatial Information Science with Honours at the School of Geography and Environmental Studies, University of Tasmania (October, 2007).

## **Declaration**

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This thesis contains no material which has been accepted for the award of any other degree or diploma in any tertiary institution, and to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

Signed

A handwritten signature in blue ink, appearing to read 'Samya Jabbour', with a long horizontal stroke extending to the right.

Samya Jabbour BSc.  
19 October 2007

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## Acknowledgments

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This project could not have been possible without the collective expertise, guidance and general goodwill of many good people. A very huge THANKYOU must first go to Arko Lucieer, *Super-visor* extraordinaire! Your calm encouragement and guidance made each week of this experience that much more possible. Thankfully, it will never be known just where my project may have wandered to if it weren't for our weekly meetings....! And to Richard Mount, the very best secondary *Super-visor* anyone could hope for! Your enthusiasm for this project and your general encouragement throughout it all meant a whole lot to me.

A big thankyou also goes to Manuel Nunez for great support in the early months of this study, and for putting me in touch with some other quite knowledgeable folk (before disappearing to Spain to lounge about in the sun!) A big thankyou also goes to Rob Musk for extensive help (and patience) while I was straining to get my head around spatial statistics. Your brain is an enigma.

To Bill Wood, Andreas Ernst and Jim Markos in Launceston for each providing considerable input and encouragement in the early stages, and for tolerating my vagueness as I struggled to find the right path for this study!

To Dr Richard Wood-Baker from the Respiratory Research branch of the Menzies Research Institute – this project would probably never have gotten off the ground in its current form without your considerable help with data acquisition, and general encouragement. Your ongoing support throughout the year has been very much appreciated. A very big thankyou must go to Mike Power at the Environment Division of DTAE, Tasmania for enormous amounts of help with everything to do with air pollution dispersion modelling in the Tamar Valley, and for so generously OFFERING TO RUN TAPM FOR ME!!! which added a very important dimension to my work that I simply wouldn't have had time to do myself. Is there enough chocolate in the world to repay you?? Huge thankyou also go to Darren Turner (UTAS) and Tony Miller (Eighty Options) for extensive help converting a concept from my head into various computer programs that drove the process of de-identification of address points.

And of course the biggest thankyou goes to Dom! For helping to keep me mostly sane this year, and for putting up with me for the rest of the time too... for nurturing our garden when I was stuck to the computer... and above all for encouraging me to follow my heart and produce meaningful work. You are an inspiration.

## **Abstract**

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The detrimental health effects of particulate air pollution have been well established through environmental health research worldwide. Fine or 'respirable' particulate matter derived from combustion sources has been linked to both acute and chronic respiratory and cardiovascular conditions, and premature death in the most susceptible of a population. The Tamar Valley in northern Tasmania has a significant winter air pollution problem. Launceston is the largest population centre in the valley (population approx. 67,000) and despite its size this small city has regularly recorded the highest levels of particulate pollution levels of any city in Australia. This is due largely to complex geographic and climatic processes that support cold air drainage and the formation of night-time temperature inversions in the valley over winter months. Under these conditions ground temperature drops and air pollution becomes trapped at ground level under a layer of dense cold air. Fine particulate matter from domestic wood heating contributes to around 88% of particulate load in Launceston compared to 65% in other Australian cities. Concern has therefore been raised for the respiratory health of Tamar Valley residents in recent years. Previous studies have assumed homogeneity of pollution exposure, and disease risk, across the landscape. This assumption is unrealistic, as recent research indicates that both the distribution of disease and the dispersal of particulate air pollution exhibit considerable spatial variation.

This is the first study to look in detail at the spatial relationships between particulate air pollution and respiratory disease distribution in the Tamar Valley. Disease clustering was investigated and various environmental processes were explored in detail to explain the spatial disparity of disease distribution. Patterns of respiratory disease occurrence in the Tamar Valley were investigated through spatial analysis of 15 years (1992-2006) of de-identified hospital admissions records. Issues of confidentiality and geoprivacy in spatial public health studies were discussed in detail. Spatial distributions of Asthma, Bronchiolitis, Bronchitis and Chronic Obstructive Pulmonary Disease (COPD) were explored individually and in combined form. Data were explored for annual variations in disease distribution. This revealed that, while disease incidence generally declined over the study period, this decline was most noticeable around George Town in the north of the valley. Further analysis revealed little spatial variation in seasonal spatial patterns of disease occurrence across the valley, though disease cases generally were more numerous in winter. COPD incidence was found to be highly clustered in a small number of address locations thought to correspond to nursing homes and aged care facilities across the valley. It was therefore believed that COPD

was more closely correlated with the locations of these facilities than with any geographic or climatic processes. Three techniques for the detection of disease clusters were applied (kernel density function, Getis Ord  $G_i^*$  statistic and Kulldorff's spatial scan statistic). Areas around George Town and the North Esk valley east of Launceston consistently showed elevated disease levels. However, considerable variation in the reporting of 'significant' clusters was noted between methods, and also with the same method at different spatial scales. Issues of statistical inference were therefore discussed.

Several 'exposure surfaces' were created to approximate the winter dispersion of particulate air pollution in Launceston. Modelled air pollution concentrations were derived from TAPM (The Air Pollution Model), a prognostic air pollution dispersion model currently in use in Tasmania for environmental monitoring purposes. A digital elevation model was also classified into terrain features that are known to accumulate high levels of particulate pollution through the process of cold air drainage (i.e. low-lying channels and river flats). Spatial relationships between disease incidence and these air pollution 'proxies' were then explored in detail. Weak relationships were found between disease incidence and terrain features representing small channel and valleys. A 'significant' relationship was found between disease incidence and the valley floor, though issues of statistical inference were again discussed in this context. Spatial non-stationarity was detected in all relationships, indicating that global statistics inadequately define these relationships. A strong *inverse* relationship was found between modelled air pollution concentrations and disease incidence, indicating that disease rates were generally higher in areas outside the modelled air pollution plume derived by TAPM. TAPM concentrations were also found to closely mirror the underlying population distribution. The inability of TAPM to adequately predict pollution levels in areas outside major population centres, and various issues of socioeconomic confounding were discussed as possible explanations for this finding.

Results generally revealed considerable variation in the spatial relationships between disease incidence and air pollution proxies used in this study. These results argue strongly for the spatial analysis of air pollution relationships to health outcomes, and the continued refinement of methods. None of these findings could have resulted from a purely temporal (non-spatial) investigation.